

Chapter 5: Continuous distributions

5.1: Density Functions

Now let's move into the realm of continuous random variables. With discrete r.v.'s, we looked at the distribution of possible outcomes by enumerating it as a list:

x	0	1	2	3
$P(\bar{X}=x)$	$\frac{1}{6}$	$\frac{1}{2}$	$\frac{1}{6}$	$\frac{1}{6}$

There are lots of phenomena that make more sense to be modeled as continuous r.v.'s: e.g.,

- height/weight of a random person in a group
- physical variables {
 - temperature
 - voltage

Let's consider how to think about the probability of outcomes of a cont. r.v.

Def:

Let \bar{X} be a cont. real-valued r.v.. A density function for \bar{X} is a real valued function, which satisfies

$$P(a \leq \bar{X} \leq b) = \int_a^b f(x) dx$$

In other words, the prob. that $\bar{X} \in [a, b]$ is given by the area under $f(x)$ from a to b .



Does not need to be closed

Note:

1. By this definition,

$$P(X=c) = \int_c^c f(x) dx = 0 \quad \forall c \in \mathbb{R}$$

2. $f(x)$ is also called the probability density function, or pdf

Question:

Which functions $f(x)$ qualify as density functions?

We want our probabilities to be non-negative, and to 'sum to one': $P(-\infty < X < \infty) = 1$. Therefore, the conditions we must place on $f(x)$ are:

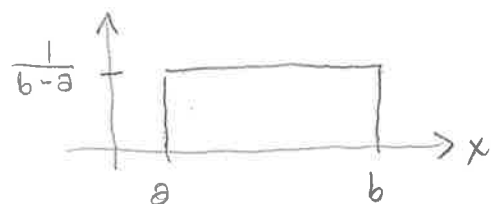
$$1. f(x) \geq 0 \quad \forall x \in \mathbb{R}$$

$$2. \int_{-\infty}^{\infty} f(x) dx = 1$$

In practice, this is how we check whether a function is a density function

Example 1:

$$\text{Let } f(x) = \begin{cases} \frac{1}{b-a} & , a \leq x \leq b \\ 0 & , \text{otherwise} \end{cases}$$



Check that it's a density function: $f(x) \geq 0$, and

$$\int_{-\infty}^{\infty} f(x) dx = \int_a^b \frac{1}{b-a} dx = \left. \frac{x}{b-a} \right|_{x=a}^b = \frac{b-a}{b-a} = 1 \quad \checkmark$$

Example 2:

$$\text{Let } f(x) = \begin{cases} \lambda e^{-\lambda x} & , x \geq 0 \\ 0 & , \text{otherwise} \end{cases}$$



$$\int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} \lambda e^{-\lambda x} dx = \lim_{t \rightarrow \infty} \int_0^t \lambda e^{-\lambda x} dx = \left(\lim_{t \rightarrow \infty} -e^{-\lambda x} \right) \Big|_{x=0}^t = \lim_{t \rightarrow \infty} (e^{-\lambda t} + 1) = 1$$

More precisely, in example 1 we saw the density function for a uniform distribution.

Def:

A random variable X has the uniform distribution on an interval $[a, b]$ if X has the density function

$$f(x) = \begin{cases} \frac{1}{b-a}, & x \in [a, b] \\ 0, & \text{otherwise} \end{cases}$$

We abbreviate this as $X \sim \text{Unif}(a, b)$ or $U(a, b)$

Similarly, if X has the density function

$$f(x) = \lambda e^{-\lambda x}, \quad x \geq 0$$

We say X has the exponential distribution. One common example of an "exp. dist." is waiting times b/w events.

* Note:

The value of a density function is not a probability. For the uniform distribution, $f(x)$ can be greater than 1

if, e.g. $b-a < 1$:



5.2: Distribution functionsDefinition:

A r.v. (continuous, discrete, or in between) has a distribution function defined by $F(x) = P(X \leq x)$. If X has a density function $f(x)$, then

$$F(x) = P(-\infty < X \leq x) = \int_{-\infty}^x f(t) dt$$

Note:

$F(x)$ is aka the cumulative distribution function, or cdf.

The Return of FTC:

The distribution function gives use a nice property:
note that for $a < b$,

$$P(X \leq b) = P(X \leq a) + P(a < X \leq b)$$

$$\begin{aligned} \Rightarrow \underbrace{P(a < X \leq b)} &= \underbrace{P(X \leq b) - P(X \leq a)} \\ &= \int_a^b f(x) dx &= F(b) - F(a) \end{aligned}$$

$$\Rightarrow \int_a^b f(x) dx = F(b) - F(a)$$

Properties:

1. Nondecreasing: if $x_1 < x_2$, then $F(x_1) \leq F(x_2)$

2. Limits at $\pm\infty$: $\lim_{x \rightarrow -\infty} F(x) = 0$ and $\lim_{x \rightarrow \infty} F(x) = 1$.

Example:

Find $F(x)$ for the exponential distribution;

we have that the density function is: $f(x) = \lambda e^{-\lambda x}$, $x \geq 0$.

Then

$$F(x) = \int_{-\infty}^x f(t) dt = \begin{cases} \int_{-\infty}^x 0 dt, & x \leq 0 \\ \int_0^x \lambda e^{-\lambda t} dt, & x \geq 0 \end{cases}$$

$$= \begin{cases} 0, & x \leq 0 \\ -e^{-\lambda t} \Big|_{t=0}^x, & x \geq 0 \end{cases}$$

$$= \begin{cases} 0, & x \leq 0 \\ -e^{-\lambda x} + 1, & x \geq 0 \end{cases}$$

↖ see why equality ↙

Note: This says that $P(X \leq x) = 1 - e^{-\lambda x}$, so $P(X > x) = 1 - F(x) = e^{-\lambda x}$.

Memoryless Prop → The exponential distribution lacks memory (or has the memoryless property): suppose T has an exponential dist. w/ par. λ . Then

$$\begin{aligned} P(T > t+s \mid T > t) &= \frac{P(\{T > t+s\} \cap \{T > t\})}{P(T > t)} = \frac{P(T > t+s)}{P(T > t)} \\ &= \frac{e^{-\lambda(t+s)}}{e^{-\lambda t}} = e^{-\lambda s} \\ &= P(T > s) \end{aligned}$$

Ex: wait time if arrive at time t or time s has same prob.

Extensions of density + dist. fn's (5.1+5.2)

Recall:

Given a discrete r.v. \bar{X} and a function $r(x)$, the expected value of $r(\bar{X})$ is

$$E r(\bar{X}) = \sum_x r(x) P(\bar{X} = x)$$

Def:

The expected value of a function of a continuous r.v. $r(\bar{X})$ is

$$E r(\bar{X}) = \int_{-\infty}^{\infty} r(x) f(x) dx$$

Note:

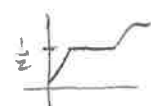
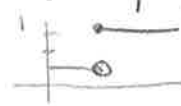
Moments and variance are defined as with discrete r.v.'s:
for a contx r.v. \bar{X} ,

$r(x) = x^k \Rightarrow E \bar{X}^k$ is the k^{th} moment

$$\text{var}(\bar{X}) = E(\bar{X} - E\bar{X})^2 = E\bar{X}^2 - (E\bar{X})^2$$

Now let's talk about median. Intuitively, the median is the value of the distribution $F(x)$ for which $F(x)$

crosses $\frac{1}{2}$. But $\{x : F(x) = \frac{1}{2}\}$ may be empty or contain ≥ 1 point



Definition:

A value m is a median for F is $P(X \leq m) \geq \frac{1}{2}$ and $P(X \geq m) \geq \frac{1}{2}$

EX:

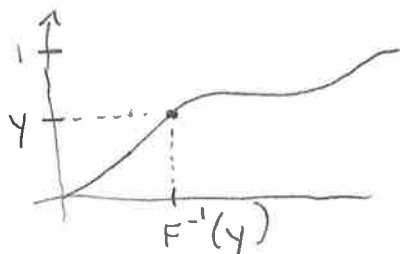
Inverse of cdf: the inverse of the cdf can be extremely useful if you're doing any statistical analysis of data.

Def:

The inverse distribution function (icdf), aka the quantile function, is the inverse of the distribution function $F(x)$:

$$F^{-1}(y) = \min\{x \mid F(x) \geq y\}$$

visually,



Why is this important? Because this gives us a way to draw randomly from any distribution, due to these pair of results:

Theorem 5.2:

Suppose $f(x)$ has a continuous distribution. Then

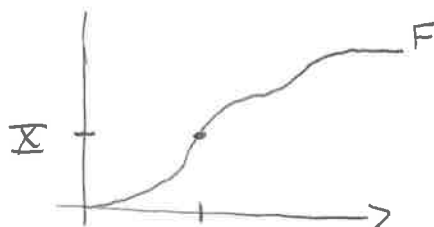
$$Y = F(\bar{X}) \sim \text{Unif}(0, 1)$$

$$\text{i.e., } P(F(\bar{X}) < y) = P(\bar{X} < F^{-1}(y)) = F(F^{-1}(y)) = y$$

Theorem 5.3:

Suppose $U \sim \text{Unif}(0, 1)$. Then $X = F^{-1}(U)$ has the distribution function F .

So if you want to draw randomly from a general (even data) distr., simply draw an $X \sim \text{Unif}(0, 1)$ and find the value of the distribution that matches it



$F^{-1}(X)$ is the random number sampled from the distribution F

Example:

$$1 - e^{-\lambda x} = y \Rightarrow x = -\frac{\ln|1-y|}{\lambda} \Rightarrow U \sim \text{Unif}(0, 1) \Rightarrow -\frac{\ln|1-U|}{\lambda} \text{ has the exp. dist.}$$

Section 5.3: Functions of r.v.'s

Question:

What do we mean by distributions (and densities) of functions of r.v.'s?

EX:

Suppose $X \sim \text{Exp}(\lambda)$. What is dist. fn of $Y = X^2$?

Recall $P(X \leq x) = 1 - e^{-\lambda x}$.

$$\Rightarrow P(Y \leq y) = P(X^2 \leq y) = P(X \leq \sqrt{y}) = 1 - e^{-\lambda\sqrt{y}}, \quad y \geq 0$$

The density function is then the derivative wrt y :

$$f_Y(y) = \frac{d}{dy} P(Y \leq y) = \frac{\lambda}{2\sqrt{y}} e^{-\lambda\sqrt{y}}, \quad y \geq 0$$

In general, we can find the density of a fn. of a r.v. by differentiating.

Theorem:

Suppose X has the density f and $P(a < X < b) = 1$. Let

$Y = r(X)$, where $r: (a, b) \rightarrow (\alpha, \beta)$ is cont. & strictly inc.

Let $s: (\alpha, \beta) \rightarrow (a, b)$ be the inverse of r . Then Y

has density

$$g(y) = f(s(y)) s'(y), \quad y \in (\alpha, \beta)$$

* Do example using this explicitly

Section 5.4: Joint Distributions

For functions of two random variables.

Def:

Two r.v.'s X and Y are said to have joint density function $f(x,y)$ if $\forall A \subset \mathbb{R}^2$,

$$P((X,Y) \in A) = \iint_A f(x,y) dx dy,$$

where $f(x,y) \geq 0$ and $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy = 1$

Double integrals (aka iterated integrals)

Suppose $f(x,y) = x^2 + y^2$

$$\begin{aligned} \iint f(x,y) dx dy &= \iint (x^2 + y^2) dx dy = \int \left(\int x^2 + y^2 dx \right) dy = \int \left(\frac{1}{3}x^3 + y^2 x \right) dy \\ &= \frac{1}{3}x^3 y + \frac{1}{3}y^3 x + c \end{aligned}$$

$f(x,y) = xy$

$$\begin{aligned} \iint xy dx dy &= \int \left(\int xy dx \right) dy = \int y \int x dx dy \\ &= \int y \left(\frac{1}{2}x^2 \right) dy = \frac{1}{2}y^2 \left(\frac{1}{2}x^2 \right) + c = \frac{1}{4}x^2 y^2 + c \end{aligned}$$

Example:Consider $f(x,y) = e^{-y}$, $0 < x < y < \infty$ f is a density fn:

$$f(x,y) \geq 0 \quad \forall x,y$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x,y) dx dy = \int_0^{\infty} \int_0^y e^{-y} dx dy$$

$$\int_0^y e^{-y} dx = xe^{-y} \Big|_{x=0}^y$$

$$= ye^{-y} - 0$$

$$= \int_0^{\infty} ye^{-y} dy$$

$$= \lim_{t \rightarrow \infty} \int_0^t ye^{-y} dy$$

$$u = y \quad v = -e^{-y}$$

$$du = dy \quad dv = e^{-y} dy$$

$$= \lim_{t \rightarrow \infty} \left[-ye^{-y} \Big|_{y=0}^t + \int_0^t e^{-y} dy \right]$$

$$= \lim_{t \rightarrow \infty} \left[-\left(\frac{t}{e^t} - 0\right) - e^{-y} \Big|_{y=0}^t \right]$$

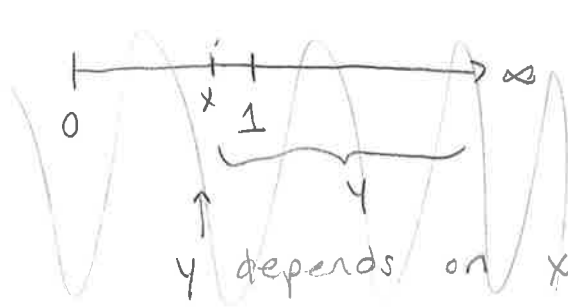
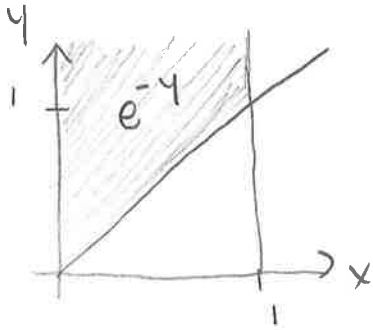
$$= -\lim_{t \rightarrow \infty} \frac{t}{e^t} - \lim_{t \rightarrow \infty} \left(\frac{1}{e^t} - e^0 \right)$$

$$= -\lim_{t \rightarrow \infty} \frac{1}{e^t} - (0 - 1)$$

$$= 1$$

Now suppose we WTF $P(X \leq 1) = P((X, Y) \in A)$, $A = \{(x, y) \mid x \leq 1\}$.

$$P(X \leq x) = \int \int e^{-y} d d$$



$$(0 < x < y < \infty)$$

$$= \int_0^1 \int_x^\infty e^{-y} dy dx$$

$$\begin{aligned} \int_x^\infty e^{-y} dy &= \lim_{t \rightarrow \infty} \int_x^t e^{-y} dy \\ &= \lim_{t \rightarrow \infty} -e^{-y} \Big|_x^t \\ &= \lim_{t \rightarrow \infty} -\left(\frac{1}{e^t} - \frac{1}{e^x}\right) \\ &= \frac{1}{e^x} \end{aligned}$$

$$= \int_0^1 e^{-x} dx = -e^{-x} \Big|_{x=0}^1 = -(e^{-1} - e^0) = -\frac{1}{e} + 1$$

Now, given a distribution function, how do we find the joint density?
distribution?

We describe joint distribution functions using

$$F(x, y) = P(X \leq x, Y \leq y)$$

Ex.

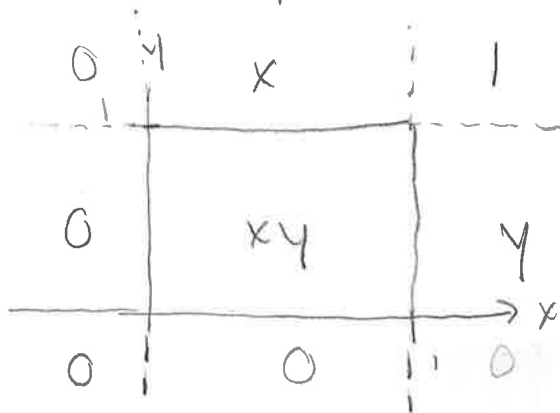
Suppose (X, Y) is unif. dist. over the square
 $\{(x, y) \mid 0 < x < 1, 0 < y < 1\}$. i.e.,

$$f(x, y) = 1, \quad 0 < x, y < 1$$

The dist. function needs to be found in pieces,

For $0 \leq x \leq 1$ and $0 \leq y \leq 1$:

$$\begin{aligned} P(X \leq x, Y \leq y) &= \int_0^x \int_0^y 1 \, dv \, du \\ &= xy \\ &= F(x, y) \end{aligned}$$



For $0 \leq x \leq 1$ and $y \geq 1$

$$P(X \leq x, Y \leq y) = P(X \leq x, Y \leq 1) = F(x, 1) = x$$

For $x \geq 1$, $0 \leq y \leq 1$

$$P(X \leq x, Y \leq y) = F(1, y) = y$$

For $x \geq 1$, $y \geq 1$

$$F(1, 1) = 1$$

$$\Rightarrow F(x, y) = \begin{cases} 0, & x < 0 \text{ or } y < 0 \\ xy, & \\ x, & \\ y, & \\ 1, & \end{cases}$$

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Outside of the unit square?

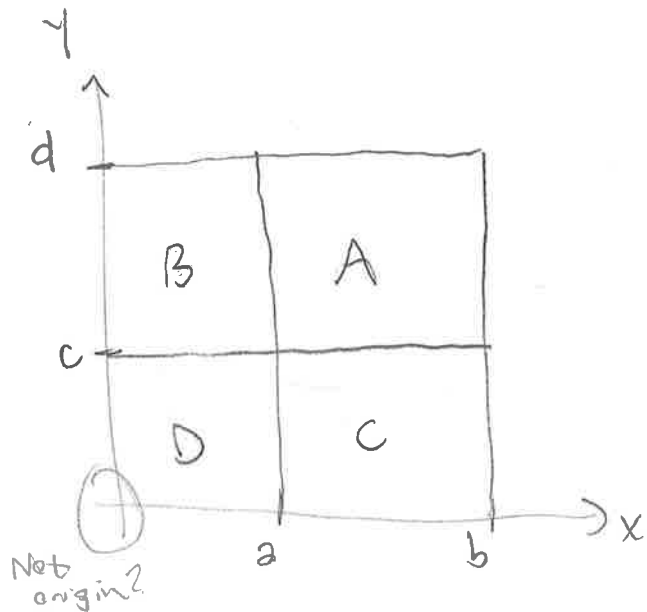
$$P(a, < X < b, c, < Y < d)$$

$$= F(b, d)$$

$$- F(a, d)$$

$$- F(b, c)$$

$$+ F(a, c)$$



$$F(b, d) = A + B + C + D$$

$$- F(a, d) = -B - D$$

$$- F(b, c) = -C - D$$

$$+ F(a, c) = D$$

The joint density fun.

$$F(x, y) = \int_{-\infty}^x \int_{-\infty}^y f(u, v) dv du$$

$$\frac{\partial^2 F}{\partial x \partial y} = f$$

Section 5.5: Marginal and conditional distributions

Recall: for discrete r.v.'s, the marginal distributions can be obtained from a joint distribution by summing

$$P(\mathbb{X}=x) = \sum_Y P(\{\mathbb{X}=x\} \cap \{\mathbb{Y}=y\}) = \sum_Y P(\mathbb{X}=x, \mathbb{Y}=y)$$

$$P(\mathbb{Y}=y) = \sum_X P(\mathbb{X}=x, \mathbb{Y}=y)$$

Note: marginal cdf is
 $F_{\mathbb{X}} = F_{\mathbb{X}\mathbb{Y}}(x, \infty) = \lim_{y \rightarrow \infty} F_{\mathbb{X}\mathbb{Y}}(x, y)$

Definition:

If the continuous r.v.'s \mathbb{X} and \mathbb{Y} have joint density $f(x, y)$, then the marginal densities of \mathbb{X} and \mathbb{Y} are given by

$$f_{\mathbb{X}}(x) = \int_{-\infty}^{\infty} f(x, y) dy \quad \text{and} \quad f_{\mathbb{Y}}(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

Note:

Similarly to finding $P(\mathbb{X}=x)$, the marginal distribution for a discrete r.v. (actually, this is more appropriately defined as the probability mass function), we 'sum' over one of the variables and obtain a function for the other variable

Example:

Let \mathbb{X} and \mathbb{Y} have joint density function $f(x, y) = x + y$, for $0 < x < 1$ and $0 < y < 1$. Then the marginal density of \mathbb{X}

is

$$f_{\mathbb{X}}(x) = \int_0^1 (x+y) dy = (xy + \frac{1}{2}y^2) \Big|_{y=0}^1 = x + \frac{1}{2}, \quad 0 \leq x \leq 1$$

and \mathbb{Y} is

$$f_{\mathbb{Y}}(y) = \int_0^1 (x+y) dx = y + \frac{1}{2}, \quad 0 \leq y \leq 1$$

Question:Are X and Y independent?Def:Two continuous r.v.'s X and Y are independent if

$$\underbrace{f(x,y)}_{\text{joint density}} = \underbrace{f_X(x) f_Y(y)}_{\text{marginal densities}}$$

Back to example:

$$f(x,y) = x+y$$

$$f_X f_Y = (x + \frac{1}{2})(y + \frac{1}{2}) = xy + \frac{1}{2}(x+y) + \frac{1}{4} \neq x+y, \quad x,y \in [0,1]$$

$\rightarrow X$ and Y are dependent.

Ex:

$$f(x,y) = \frac{y^{-3/2} \cos x}{e-1} e^{\sin x - \frac{2}{\sqrt{y}}}, \quad 0 < x < \frac{\pi}{2}, \quad y > 0$$

We could integrate this, but there's a simpler approach:

Theorem:If the joint density function $f(x,y)$ can be written as $g(x)h(y)$, then there is a constant c s.t.

$$f_X(x) = cg(x)$$

$$f_Y(y) = \frac{h(y)}{c}$$

Then $f(x,y) = f_X(x) f_Y(y)$, and is thus independent.

Back to example:

$$f(x,y) = \underbrace{\frac{\cos x e^{\sin x}}{e-1}}_{g(x)} \underbrace{\left(y^{-3/2} e^{-2/\sqrt{y}} \right)}_{h(y)}$$

Question:Where does the c come in?

← worksheet

Proof of Theorem:

$$f_X(x) = \int_{-\infty}^{\infty} f(x,y) dy = \int g(x) h(y) dy = g(x) \underbrace{\int h(y) dy}_{\equiv c}$$

$$f_Y(y) = \int_{-\infty}^{\infty} f(x,y) dx = h(y) \underbrace{\int g(x) dx}_{\frac{1}{c} ?}$$

$$1 = \iint f(x,y) dx dy = \int g(x) dx \int h(y) dy \Rightarrow \int g(x) dx = \frac{1}{c} \quad \checkmark$$

Now let's look at conditional distributions. Again, recall the discrete case:

$$P(X=x | Y=y) = \frac{P(X=x, Y=y)}{P(Y=y)} \quad \leftarrow \text{joint distribution}$$

← marginal distribution
prob. mass function
density

For the continuous case, we need the concept of a conditional density.

recall: think Force →
medications

Def:

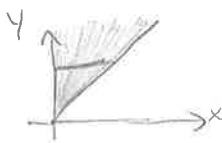
The conditional density of X , given $Y=y$, is

$$f_X(x | Y=y) = \frac{f(x,y)}{f_Y(y)} = \frac{f(x,y)}{\int f(t,y) dt} \quad \leftarrow \text{joint density}$$

← marginal density

Example:

$$f(x,y) = e^{-y} \quad 0 \leq x \leq y < \infty$$



$$f_X(x | Y=y) = \frac{e^{-y}}{f_Y(y)} \quad , \quad f_Y(y) = \int_0^y e^{-y} dx = xe^{-y} \Big|_{x=0}^y = ye^{-y}$$

$$= \frac{e^{-y}}{ye^{-y}} = \frac{1}{y} \quad , \quad 0 < x < y$$

And

$$f_{\mathcal{Y}}(y | \mathcal{X}=x) = \frac{f(x,y)}{f_{\mathcal{X}}(x)}$$

$$= \frac{e^{-y}}{e^{-x}}$$

$$= e^{-(y-x)}, \quad y \geq x$$

$$f_{\mathcal{X}}(x) = \int_x^{\infty} e^{-y} dy = \lim_{s \rightarrow \infty} \int_x^s e^{-y} dy$$

$$= \lim_{s \rightarrow \infty} -e^{-y} \Big|_{y=x}^s$$

$$= \lim_{s \rightarrow \infty} \left(-\frac{1}{e^s} + e^{-x} \right)$$

Note:

We can use the definition of conditional and marginal densities to obtain the joint density:

$$f(x,y) = f_{\mathcal{X}}(x) f_{\mathcal{Y}}(y | \mathcal{X}=x) = f_{\mathcal{Y}}(y) f_{\mathcal{X}}(x | \mathcal{Y}=y)$$

Question:

For $f(x,y) = e^{-y}$, are \mathcal{X} and \mathcal{Y} independent?

No:

$$e^{-y} \neq y e^{-y} e^{-x}$$

aka the support

In general, if the region where $f(x,y) > 0$ is not a rectangle, then \mathcal{X} & \mathcal{Y} dependent. Though we've seen an example where it is a rectangle and they were still dependent